Reshaping Text Data for Efficient Processing on Amazon EC2

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Outline

- Motivation
- Goals:
 - Determine empirically simple application performance model
 - Statically provision resources to meet user constraints
 - Reshape the input to avoid the small file problem
- Approach
 - Sample Applications grep, part of speech tagging
- Summary

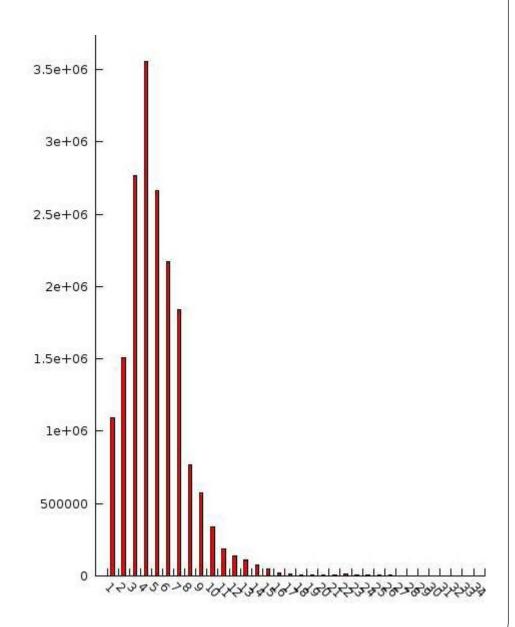
Motivation

- Analysis of large corpora
 - Online news collections
 - Text generated by social networks tweets, status updates, comments, reviews
 - Scientific article abstracts, posters, slides



Text Datasets

- Heavy tail distribution
 - Majority of files of a few KB



Text processing in the cloud

- The analysis of large corpora demands increasing computational resources:
 - Cloud computing offers benefits:
 - On-demand provisioned environment
 - Pay-as-you-go pricing model
 - Customizable virtual machines that can be easily configured to incorporate legacy software
 - ...and drawbacks:
 - Infrastructure controlled by provider
 - Environment volatility

Setting

- We have a large text workload, comprising of small files whose size distribution we know
- We do not have a model for the application performance in the cloud
- Can we construct empirically an application performance model to help provision resources within user constraints?
- Can we reshape the input data for improved performance? If so, what is the best organization?

Amazon EC2

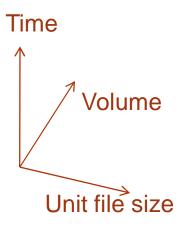
- On-demand resizable computing capacity with a pay-as-you-go pricing scheme
 - Instances (small,medium,large) with different CPU, memory and I/O performance
 - AMI (Amazon machine images) with different configuration (32/64-bit architecture, Fedora/Windows/Ubuntu)

Amazon EC2 - storage

- Ephemeral
 - Instance store 160GB for a small instance
- Persistent
 - Elastic Block Store (EBS) volumes
 - 1GB to 1TB in size
 - Exposed as raw block devices that can be 'attached' to instances
 - Cannot be shared between instances
 - Pay per GB/month and also per 1M I/O requests
 - Amazon Simple Storage Service (S3)
 - Unlimited number of objects up to 5GB each
 - Multiple instances can access this storage in parallel with low latency (though higher and more variable than EBS)

Approach

- Request instance (small, FC8) and measure its read/write performance
- Send probes of increasing volume to profile application
 - Send probe of 1 file of volume V₀: P_{_} V₀_original
 - Select larger volume V₁ as a multiple of V₀
 - Create P_V₁_original
 - Select base unit sizes (s₀,...,s_n)
 - Create P_V₁_s₀, ...,P_V₁_s_n
 using first fit binpacking
 - Repeat binpacking for each probe
 - Create P_V₁_s₀ and then merge to obtain remaining probes – sensitive to quality of s₀ probe



Approach

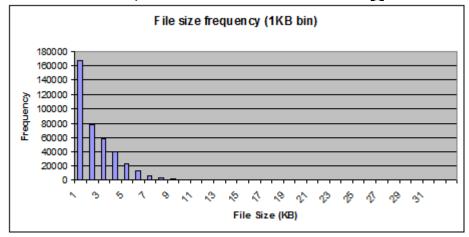
- If possible, select a unit file size that minimizes the execution time
- Reshape the data set according to match the file size as closely as possible
 - Splitting of a file not considered
- Derive a performance model as "execution time=f(vol)" performing linear regression on the measurements corresponding to the selected file size
 - Linear y=ax
 - Power law y=ax^b
 - Exponential y=ae^{bx}

Part of Speech tagging

Java implementation Stanford NLP POS tagger:

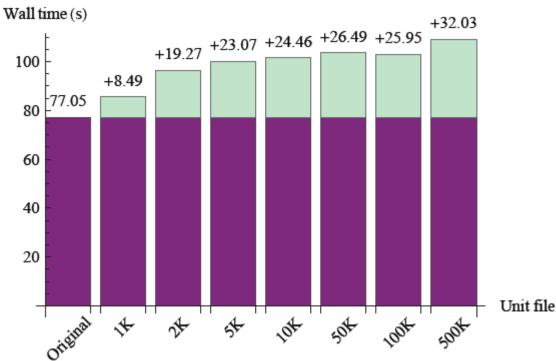
Mary_NNP has_VBZ 3_CD little_JJ lambs_NNS ._.

- Process multiple files within same JVM
- Data set:
 - 1GB of text data
 - >40% of files are <1KB
- Small instance, instance storage



POS tagging

- V=1MB
- $S_0 = 1KB, ..., S_n = 500k$



» Original size performs best

Performance Model

Linear fit

$$f(x) = 0.327 + 0.865 * 10^{-4} * x$$

- Solve for a deadline D=3600 (seconds) and obtain x₀ – the volume of data predicted to be processed within D
- For volume V, provision to meet the deadline:

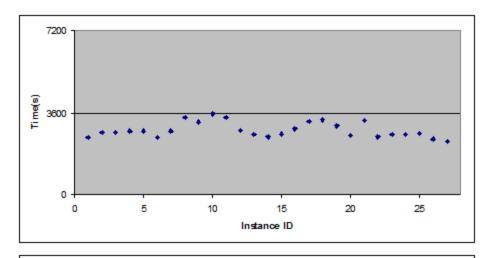
$$i_0 = \lceil \frac{V}{\lfloor x_0 \rfloor} \rceil$$

Static provisioning

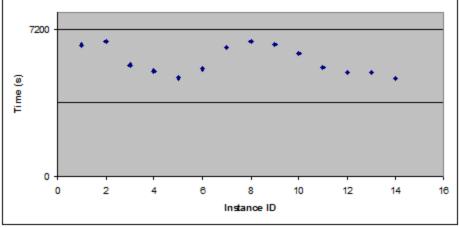
- Bin packing for i₀=27 instances:
 - Sorted by file size
 - Better fit, but fewer large files in the initial bins – performance was bad for larger files
 - Taken as presented
 - More likely to get a balance between # of files and size
 - » Other options can be explored

Initial results

• D=3600



• D=7200



» We could use fewer instances.

Random sampling

- Take random samples from the data and reevaluate performance model
- 3 samples of 5MB profile each sample

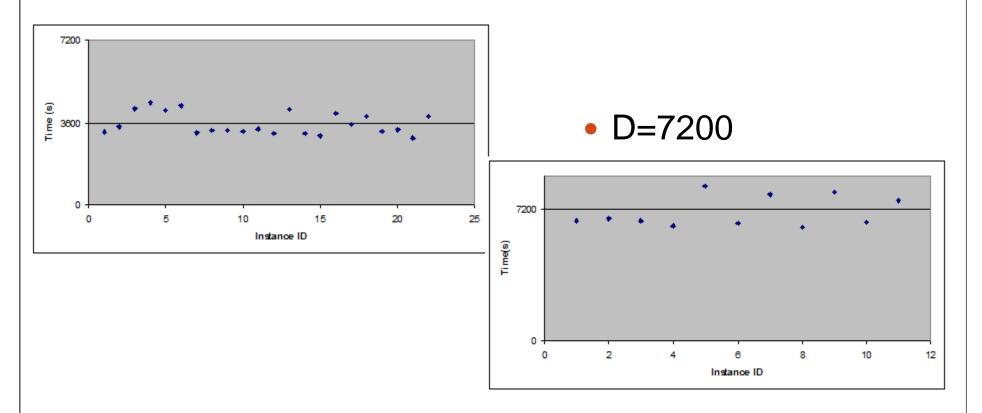
$$f(x) = 3.086 + 0.72 * 10^{-4} * x$$

The new slope is lower than the previous

$$f(x) = 0.327 + 0.865 * 10^{-4} * x$$

POS tagging – random sampling

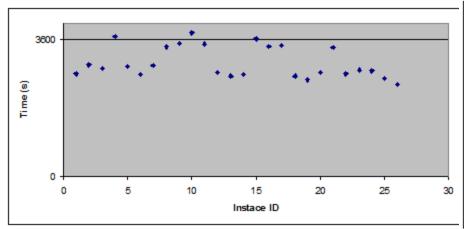
• D=3600

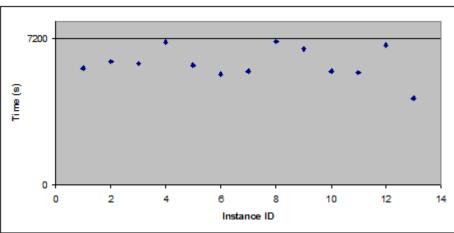


» Tighter fit, but we overshoot the deadline!

POS tagging

- We provisioned instances to exactly meet the deadline D (based on the model)
 - Residuals are can be considered normally distributed
 - Confidence interval analysis leads us to lower the deadline we provision for D=3600 -> 3124



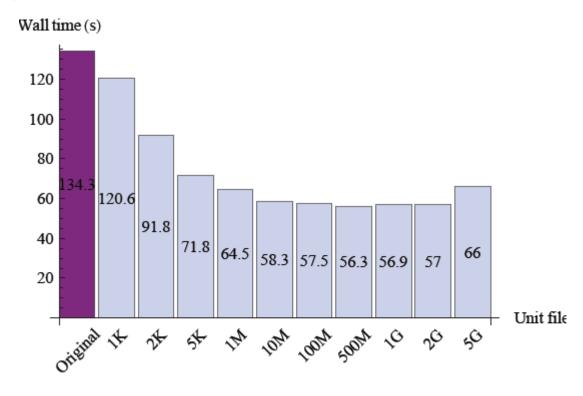


Grep

- GNU grep 2.5.1
- 100GB set of HTML files
- EBS storage
- CPU I/O mix influenced by complexity of the search pattern
 - » Search for simple patterns dictionary words
- Certain search modes and/or the likelihood of finding a match influences the amount of output generated
 - » Search for a nonsense word to traverse the entire input, but not generate output

Determining file unit size

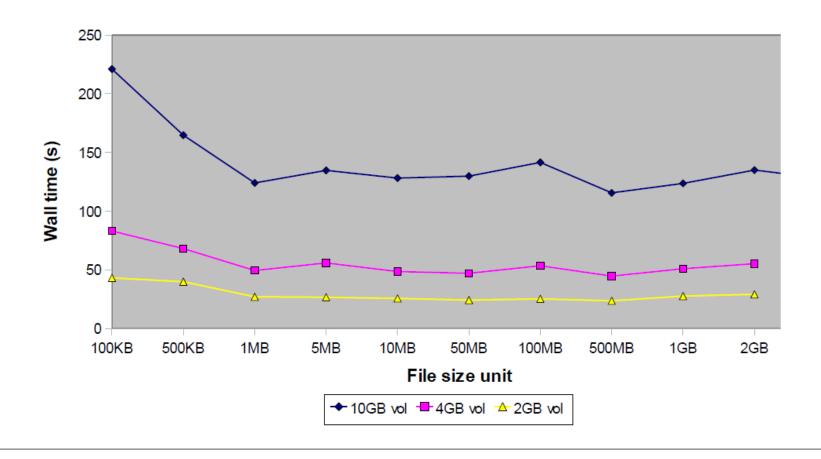
V=5GB



» 1M-2G range performs well

EBS performance

- Plateau not smooth
- EBS performance consistently worse for some data sets

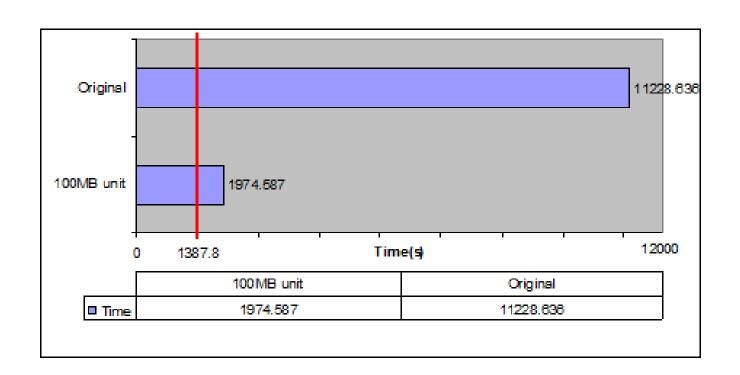


Provisioning

- If the fragment volume > predicted volume
 - Increase fragmentation level
- Othwerwise,
 - Attribute as much data to an instance as permitted by fragment volume multiples that fit into

Results

- Model: $f(x) = -0.97 + 1.32 * 10^{-8}x$
- D=3600



Summary

- Small scale experiments to learn application behavior on externally managed environment
- Determine if reshaping of input data set is beneficial
 - Grep I/O intensive, reshaped to larger file sizes
 - POS tagging memory intensive, reshaping not helpful
- Provision statically to meet user deadlines

